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# An innovative vigorous outlier recognition placed on LROAD for fix-amplitude impulsive noise

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## Article Info

## ABSTRACT

Due to large current applications on digital images in these recent years, outlier suppression is one of the primary stages for modern computer vision implementations thereupon there are tremendously invented for creating an efficient and practical outlier suppression, which ordinarily are composed of outlier recognition stage and outlier rebuilt stage. The localised rank ordered difference (LROAD) approach, which is progressed from rank-ordered absolute differences (ROAD), has been invented since 2016. Later, the LROAD approach evolved to be one of the efficient outlier recognition stages from its eminent effectiveness. The paper focus to propose the innovative vigorous outlier recognition placed on localised rank-ordered logarithmic differences (LROLD) approach, which is progressed from LROAD and (ROLD), which is higher effectiveness than the ordinary LROAD, for applying on FAIN. From the computer experiments, which are examined on many depictions such as Girl, Pepper F16 and Lena, the innovative vigorous outlier recognition placed on LROLD approach has higher eminent effectiveness then the stage-of-art approach such as LROAD and ROAD approaches at numerous consistencies of FAIN.
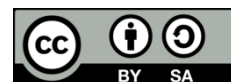
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## 1. INTRODUCTION

In computer vision and digital image processing [1], there are large current applications on digital images [2]-[4] in this recent years thereupon one of the primary stages for modern computer vision implementations [5] such as MF-SR [6], [7], SF-SR [8], face classification [9] is the outlier suppression because the sophisticated image processing approaches [5]-[9] are ordinarily sensitive on outlier. As a result, outlier suppression is one of the primary stages for modern computer vision implementations thereupon there are tremendous invented for creating practical outlier suppression approaches, which ordinarily are composed of outlier recognition stage and outlier rebuilt stage. Initially, the standard median filter (SMF) [10] was invented for FAIN in 1975 and, later, has been evolved to be one of the ordinary outlier suppression approach. For suppressing FAIN on color illustrations, the vector median filter (VMF) [11], which is progressed from ordinary SMF, was invented in 1990 and has been evolved to be one of the standard outlier suppression approach for color illustrations. Next, an adaptive median filter (AMF) [12], which was progressed from the SMF where the calculating window is self-regulating changing, was invented to be the noise suppressing algorithm for FAIN in 1994 and later, has been evolved to be one of the ordinary outlier suppression approach with superior effectiveness. In 2017, The outlier suppression approach [13] placed on both amplitude preserving cast elimination and swarm optimization was invented for exploiting color

illustrations. Thereupon, self-regulating computer-abetment investigation approach [14] placed on SVM designation for MRI brain illustrations was invented in 2017. Next, the outlier suppression approach [15] placed on outlier consistency evaluation by local statistics was invented for illustrations in 2018. Succeeding, the outlier suppression approach [16] placed on a powerful filtering approach was invented for color illustrations in 2018. Subsequently, the ordinary outlier suppression approach placed on the Gaussian filtering and Wiener filtering [17] been examined its effectiveness by changeable kernel dimension in 2019. Later, the outlier suppression approach placed on filter approach [18] been examined its effectiveness on medical illustrations in 2019. Charmouti *et al.* [19] revises tremendous outlier suppression approaches placed on different ordinary approaches and relatively reexamines this effectiveness on outlier suppression point of view in 2019. In 2020, the revised outlier suppression approach placed on an apparitional wavelet approach [20], which is the progressed from Haar wavelet as apparitional order by a LP filtering generalization with the apparitional delay process, has been invented. For underwater acoustic outlier, the outlier suppression approach placed on DWT [21] with noise density estimation was invented in 2020.

Tremendous present outlier suppression approaches [22]-[25], which are ordinarily composed of outlier recognition stage and outlier rebuilt stage, have been developed as following. In 2017, the outlier suppression approach placed on hybrid statistic method [22] is developed for suppressing impulse outlier. For high consistency of FAIN, alternative outlier suppression approach, so called adaptive decision based inverse distance weighted interpolation (DBIDWI) approach [23]-[24], which was developed for by Kishorebabu *et al.* [23] in 2017, is examined its effectiveness [24] under almost consistency of FAIN in 2019. Many present outlier recognition approaches [25] placed on rank-ordered absolute differences (ROAD), rank-ordered logarithmic differences (ROLD) and rank-ordered relative differences (RORD) are relatively reexamines for recognizing impulse outlier in 2019. Next, the outlier suppression approach placed on the triple threshold statistical detection (TTSD) filter [26] was developed for RAIN in 2018. Subsequently, the outlier suppression approach placed on the localised rank ordered absolute differences (LROAD) filter [27], which is progressed from the ordinary ROAD approach, initially was developed for RAIN in 2016 and these approach provides superior effectiveness. Consequently, the paper focus to propose the innovative vigorous outlier recognition placed on localised rank-ordered logarithmic differences (LROLD) approach [28], which is progressed from LROAD and rank-ordered logarithmic differences (ROLD), which is higher effectiveness than LROAD for FAIN.

## 2. THE PROPOSED LROLD ALGORITHM

Under FAIN situation, especially the salt-and-pepper outlier, the outlier illustration $\underline{Y}$, which is ordinarily characterized from the outlier-less illustration $\underline{X}$, is scientifically indicated in the successive algebraic testimony.

$$\underline{Y} = \underline{X} + \underline{N} \qquad (1)$$

The analytical data processing of the proposed LROLD algorithm approach for outlier recognition stage as successive:

a. For each processed illustration component $y(i,j)$ in the anormaly illustration $\underline{Y}$, the $5 \times 5$ local neighbornood group of the processed illustration component is scientifically indicated in the successive algebraic testimony as $\boldsymbol{\Omega}_{5\times5}$ where this local neighbornood group $\boldsymbol{\Omega}_{5\times5}$ is detached into nine $3 \times 3$ local neighbornood groups as $\{\boldsymbol{\Omega}_{1x}, \boldsymbol{\Omega}_{2x}, \boldsymbol{\Omega}_{3x}, \dots, \boldsymbol{\Omega}_{9x}\}$ as indicating in the Figure 1.

b. The absolute value of the subtraction between the processed illustration component $y(i,j)$ and each illustration component in each $3 \times 3$ local neighbornood groups $(\{\boldsymbol{\Omega}_{1x}, \boldsymbol{\Omega}_{2x}, \boldsymbol{\Omega}_{3x}, \dots, \boldsymbol{\Omega}_{9x}\})$ is scientifically indicated in the successive algebraic testimony.

$$d_{x,y}^k = \left| y_{\boldsymbol{\Omega}_{3\times3}} - y(i,j) \right|, \quad y_{\boldsymbol{\Omega}_{3\times3}} \in \boldsymbol{\Omega}_{kx} \qquad (2)$$

Next, the logarithmic distance value of each processed absolute value $d_{x,y}^k$ is scientifically indicated in the successive algebraic testimony.

$$d_{x,y}^k = 1 + \frac{1}{5}\left(max\left(log_2\left(d_{x,y}^k\right), -5\right)\right) \qquad (3)$$

Later, each processed logarithmic absolute value $d_{x,y}^k$ is ascendingly categorized as the successive algebraic testimony.

$$\underset{\text{ascending}}{Sort}\left(d_{x,y}^k\right) = d_{x,y}^k(1) \leq d_{x,y}^k(2) \leq d_{x,y}^k(3) \leq \cdots \leq d_{x,y}^k(8) \qquad (4)$$

c. Each ascendingly categorized values is used to process the LROLD for each $3 \times 3$ local neighbornood group ($\{\boldsymbol{\Omega}_{1x}, \boldsymbol{\Omega}_{2x}, \boldsymbol{\Omega}_{3x}, \dots, \boldsymbol{\Omega}_{9x}\}$) as the successive algebraic testimony.

$$\text{LROLD}_m^k(x) = \sum_{i=1}^m d_{x,y}^k(i) \tag{5}$$

d. Next, each $3 \times 3$ local neighbornood group $\boldsymbol{\Omega}_{kx}$ is recognized as identification to each processed illustration component $y(i,j)$ where the value $\text{LROLD}_m^k(x)$ of $3 \times 3$ regional window $\boldsymbol{\Omega}_{kx}$ is lower than the preset value ($d_T$) otherwise that $3 \times 3$ local neighbornood group $\boldsymbol{\Omega}_{kx}$ is recognized as non-identification.

e. Each processed illustration component $y(i,j)$ is recognized as an outlier illustration component where the total $3 \times 3$ local neighbornood group $\boldsymbol{\Omega}_{kx}$ is recognized as identification lower than 3 group otherwise the processed illustration component $y(i,j)$ is recognized as a outlier-less illustration component.

The comprehensive analytical data processing of the LROLD approach for outlier recognition is indicated as Figure 2 (see in appendix).
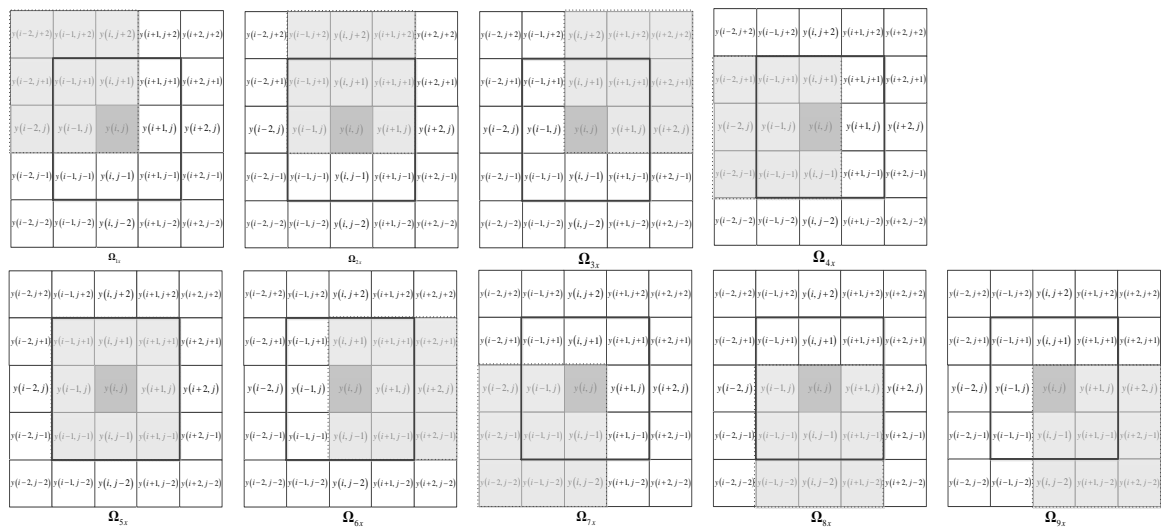


Figure 1. The organization of $3 \times 3$ local neighbornood group of LROLD

## 3. THE SCIENTIFIC PROCESS EXAMPLES OF LROLD APPROACH

This scientific part focuses to the detail process of LROLD approach. This example of LROLD approach process is indicated as Figure 3 (see in appendix) where the processed illustration component $y(i,j) = 255$ is outlier. First, the processed illustration is separatedly processed only on $5 \times 5$ local neighbornood group and, later, separately processed on nine $3 \times 3$ local neighbornood groups to be the similarity index and the processed illustration component $y(i,j)$ is recognized as outlier illustration component.

## 4. THE SCIENTIFIC RESULTS AND DISCUSSIONS

For this scientific part, the analytical computer program is the MATLAB software, which is performed on tremendous microcomputers with hardware blueprint: MPU is i7-6700HQ and primary data storage is 16 GB. Each microcomputers performs on these many illustrations (such as Girl, Lena, Pepper and F16), which are degraded by incorporating with FAIN at numerous consistency. In the first scientific experiment, the first and second moment statistical specifications of the outlier-less illustration components and outlier illustration components (from 90% to 5%) are performed by the ordinary LROAD outlier recognition approach of Girl, Lena, Pepper and F16 as indicating in the Figure 4(a), 4(c), 4(e) and 4(g) , respectively, which is compared with, the proposed LROLD outlier recognition approach of Girl, Lena, Pepper and F16 as indicating in the Figure 4(b), 4(d), 4(f) and 4(h), respectively (see in appendix). From these results, the proposed LROLD distribution of the outlier-less illustration components and outlier illustration components can remarkably recognize whether illustration components are outlier or outlier-less during the outlier consistency 5% - 60% but the proposed LROLD distribution cannot recognize when the

outlier consistency is more than 70%. In the second scientific experiment, the LROLD outlier recognition effectiveness, which is performed by (6), of Girl, Lena and Pepper (from 5% to 60%) are indicated in the Tables 1-3, respectively. Moreover, the ordinary AMF and LROAD outlier recognition effectiveness are used to compare the recognition effectiveness. From these results, the proposed LROLD distribution provides the superior recognition effectiveness at all outlier consistency between 5% - 60%. In the third scientific experiment, for exploring the overall proposed outlier suppression effectiveness, the ordinary GF, SMF, BF, AMF and LROAD outlier suppression effectiveness are used to compare the reconstruction effectiveness of Girl, Lena and Pepper (during the outlier consistency 5% - 60%) are indicated in the Tables 4-6, respectively. From these results in the Tables 4-6, the proposed LROLD outlier reconstruction provides the superior effectiveness for quantitative measurement index (PSNR) than other previouse compared outlier suppression algorithms (GF, SMF, BF, AMF and LROAD).

$$Accuracy = \frac{1}{2}\left(\left(\frac{\text{number of estimated noisy pixels}}{\text{number of noisy pixels}}\right) + \left(\frac{\text{number of estimated noiseless pixels}}{\text{number of noiseless pixels}}\right)\right) \tag{6}$$

Table 1. The outlier recognition effectiveness: Girl

| Outlier recognition | Outlier consistency (%) | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 5 | 10 | 15 | 20 | 25 | 30 | 35 | 40 | 45 | 50 | 55 | 60 |
| AMF | 0.7363 | 0.6910 | 0.6558 | 0.6209 | 0.5880 | 0.5632 | 0.5381 | 0.5217 | 0.5021 | 0.4827 | 0.4677 | 0.4516 |
| LROAD | 0.8532 | 0.8498 | 0.8413 | 0.8391 | 0.8383 | 0.8285 | 0.8181 | 0.8004 | 0.7839 | 0.7566 | 0.7319 | 0.7053 |
| LROLD | 0.8573 | 0.8538 | 0.8455 | 0.8450 | 0.8441 | 0.8379 | 0.8316 | 0.8209 | 0.8091 | 0.7927 | 0.7728 | 0.7496 |

Table 2. The outlier recognition effectiveness: Lena

| Outlier recognition | Outlier consistency (%) | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 5 | 10 | 15 | 20 | 25 | 30 | 35 | 40 | 45 | 50 | 55 | 60 |
| AMF | 0.8395 | 0.8133 | 0.7896 | 0.7650 | 0.7428 | 0.7233 | 0.7049 | 0.6920 | 0.6773 | 0.6624 | 0.6486 | 0.6373 |
| LROAD | 0.9978 | 0.9960 | 0.9942 | 0.9853 | 0.9761 | 0.9604 | 0.9420 | 0.9219 | 0.8838 | 0.8422 | 0.7868 | 0.7157 |
| LROLD | 0.9979 | 0.9949 | 0.9915 | 0.9851 | 0.9796 | 0.9682 | 0.9492 | 0.9258 | 0.8874 | 0.8445 | 0.7993 | 0.7419 |

Table 3. The outlier recognition effectiveness: Pepper

| Outlier recognition | Outlier consistency (%) | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 5 | 10 | 15 | 20 | 25 | 30 | 35 | 40 | 45 | 50 | 55 | 60 |
| AMF | 0.8550 | 0.8189 | 0.7893 | 0.7638 | 0.7368 | 0.7191 | 0.7002 | 0.6819 | 0.6653 | 0.6539 | 0.6411 | 0.6263 |
| LROAD | 0.9926 | 0.9913 | 0.9816 | 0.9734 | 0.9642 | 0.9556 | 0.9374 | 0.9108 | 0.8749 | 0.8266 | 0.7727 | 0.7002 |
| LROLD | 0.9941 | 0.9912 | 0.9856 | 0.9802 | 0.9672 | 0.9577 | 0.9407 | 0.9123 | 0.8794 | 0.8359 | 0.7916 | 0.7328 |

Table 4. The comparison consequences of the proposed outlier recognition algorithm (PSNR): Girl

| Outlier recognition | PSNR (dB) | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 5 | 10 | 15 | 20 | 25 | 30 | 35 | 40 | 45 | 50 | 55 | 60 |
| Outlier image | 16.4490 | 13.6890 | 11.9287 | 10.6567 | 9.5498 | 8.8677 | 8.0984 | 7.5798 | 7.0728 | 6.5712 | 6.2085 | 5.8609 |
| GF (3x3) | 20.0454 | 17.2530 | 15.3515 | 13.9593 | 12.7248 | 11.9599 | 11.0501 | 10.4543 | 9.8471 | 9.2367 | 8.7895 | 8.3590 |
| SMF (3x3) | 32.4867 | 31.5583 | 27.6179 | 25.5153 | 22.9614 | 20.7738 | 18.441 | 16.5146 | 14.8145 | 13.0319 | 11.8226 | 10.4981 |
| BF (bilateral filter) | 25.0465 | 21.6288 | 18.649 | 16.4313 | 14.4659 | 13.2611 | 11.9108 | 11.0055 | 10.1288 | 9.2885 | 8.6809 | 8.1088 |
| AMF (5x5) | 37.5895 | 36.9197 | 34.4478 | 31.1837 | 28.4091 | 26.2925 | 23.532 | 21.7295 | 19.9573 | 17.8279 | 16.5229 | 14.9128 |
| LROAD | 39.4510 | 36.9332 | 35.2214 | 31.4844 | 28.5135 | 24.7323 | 21.4113 | 18.5755 | 16.5495 | 14.1005 | 12.5879 | 11.0750 |
| LROLD | 39.9704 | 37.5537 | 35.8474 | 33.4131 | 31.7502 | 28.7866 | 26.1867 | 23.1084 | 20.7034 | 18.2121 | 16.3151 | 14.3784 |

Table 5. The comparison consequences of the proposed outlier recognition algorithm (PSNR): LENA

| Outlier recognition | PSNR (dB) | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 5 | 10 | 15 | 20 | 25 | 30 | 35 | 40 | 45 | 50 | 55 | 60 |
| Outlier image | 18.7139 | 15.6564 | 13.8274 | 12.6389 | 11.6783 | 10.8971 | 10.224 | 9.6481 | 9.0745 | 8.6553 | 8.2118 | 7.7813 |
| GF (Gausian filter) | 22.4181 | 19.3812 | 17.5385 | 16.3208 | 15.3526 | 14.5829 | 13.8785 | 13.2479 | 12.6598 | 12.2146 | 11.7609 | 11.2939 |
| SMF (median filter) | 31.6421 | 30.7076 | 29.2982 | 27.6257 | 25.4101 | 23.6811 | 20.8127 | 19.008 | 16.8389 | 15.4758 | 13.8573 | 12.328 |
| BF (Bilateral filter) | 27.5253 | 25.8091 | 24.2271 | 22.5517 | 20.9944 | 19.5225 | 18.0901 | 16.8416 | 15.5293 | 14.5831 | 13.5378 | 12.525 |
| AMF (5x5) | 36.0907 | 35.3032 | 33.7454 | 32.1558 | 29.8105 | 27.8658 | 25.6654 | 23.7869 | 21.5949 | 20.5710 | 19.4658 | 18.0481 |
| LROAD | 41.2463 | 37.6146 | 35.5349 | 32.3949 | 29.3816 | 26.9173 | 23.1573 | 20.7286 | 17.5746 | 15.8325 | 13.8569 | 12.1018 |
| LROLD | 41.6609 | 37.4668 | 35.1803 | 33.4546 | 30.9454 | 28.8877 | 25.7819 | 23.3168 | 20.3925 | 18.4624 | 16.5733 | 14.588 |

Table 6. The comparison consequences of the proposed outlier recognition algorithm (PSNR): Pepper

| Outlier recognition | PSNR (dB) | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 5 | 10 | 15 | 20 | 25 | 30 | 35 | 40 | 45 | 50 | 55 | 60 |
| Outlier image | 18.4752 | 15.3798 | 13.5570 | 12.3593 | 11.3929 | 10.6242 | 9.9742 | 9.3998 | 8.8599 | 8.3843 | 7.9930 | 7.6189 |
| GF (Gausian filter) | 22.1408 | 19.0677 | 17.2234 | 15.9804 | 14.9986 | 14.1748 | 13.5209 | 12.9076 | 12.3275 | 11.8117 | 11.3720 | 10.9563 |
| SMF (Median filter) | 32.2578 | 30.6116 | 28.847 | 26.5888 | 24.2073 | 22.0663 | 20.3774 | 18.4321 | 16.6168 | 14.8506 | 13.4655 | 12.0128 |
| BF (Bilateral filter) | 26.9352 | 25.0013 | 23.1364 | 21.4752 | 19.8178 | 18.2898 | 17.0781 | 15.9051 | 14.7393 | 13.6826 | 12.8287 | 11.9777 |
| AMF (5x5) | 37.1145 | 36.0387 | 33.6096 | 31.6485 | 29.4205 | 26.7650 | 25.5160 | 23.3923 | 21.4867 | 19.8454 | 18.3435 | 16.8082 |
| LROAD | 40.5977 | 37.8928 | 34.8313 | 32.4239 | 28.0055 | 25.6055 | 22.8024 | 20.0982 | 17.6646 | 15.3078 | 13.5889 | 11.8527 |
| LROLD | 40.3878 | 37.5492 | 34.8666 | 32.7106 | 29.3443 | 27.2038 | 25.7138 | 22.8715 | 20.4449 | 18.0574 | 16.2879 | 14.4357 |

Finally, to demonstate the visionalization effectiveness, some scientific results of Pepper images are illustrated in Figures 5(a) to (c). The ordinary SMF, AMF and LROAD outlier reconstruction effectiveness are used to compare the reconstruction effectiveness where the ordinary SMF at 20%, 25% and 30% outlier reconstruction effectiveness are indicated in the figure 5(a-2), 5(b-2), 5(c-2), respectively and the ordinary AMF at 20%, 25% and 30% outlier reconstruction effectiveness are indicated in the figure 5(a-3), 5(b-3), 5(c-3), respectively and the ordinary LROAD at 20%, 25% and 30% outlier reconstruction effectiveness are indicated in the figure 5(a-4), 5(b-4), 5(c-4), respectively. From these results, the proposed LROLD outlier reconstruction provides the superior effectiveness for both perceptional quality and engineering measured quality (PSNR and SSIM).
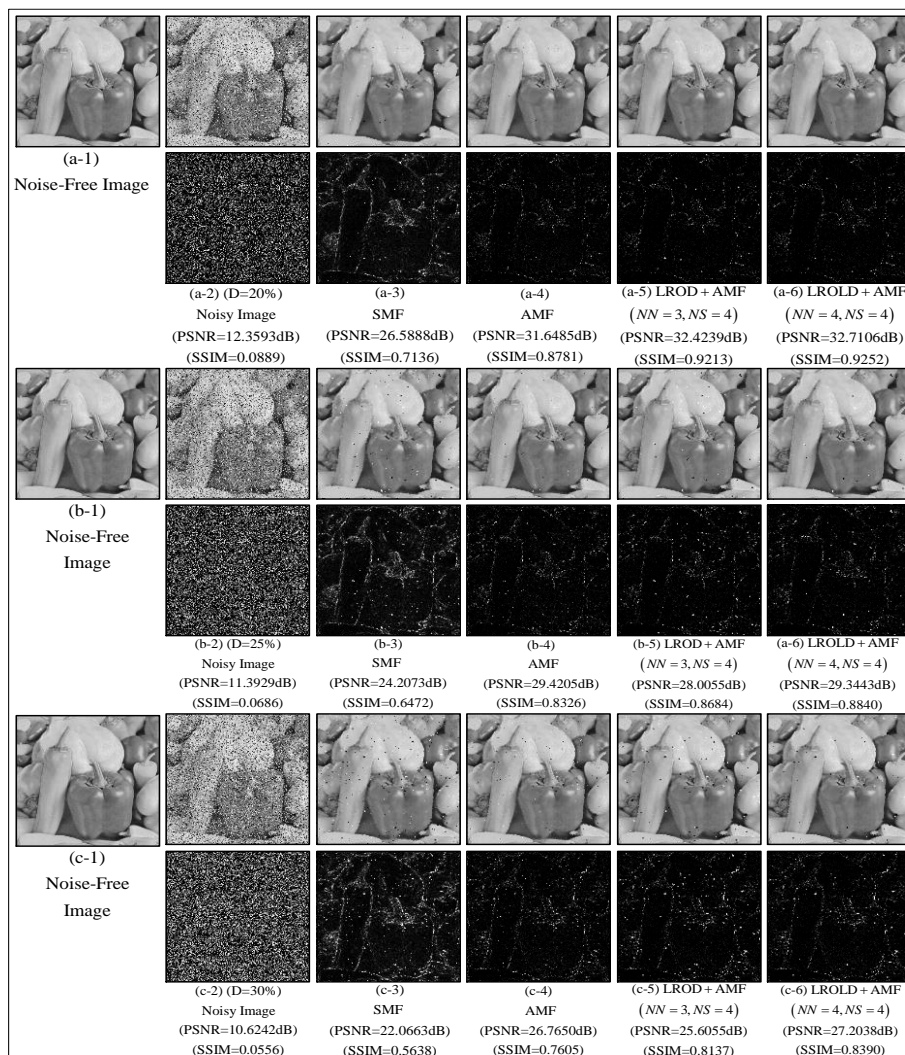


Figure 5. The comparison consequences of the scientific outlier illustrations (Pepper)

## 5. CONCLUSION

The paper focus to propose the innovative vigorous outlier recognition placed on LROAD approach, which is progressed from LROAD and ROLD, which is higher effectiveness than LROAD for FAIN. From this experimental results, the proposed LROAD outlier recognition can provide the superior effectiveness for recognizing whether illustration components are outlier or outlier-less. Therefore, the proposed LROLD outlier reconstruction provides the superior effectiveness than SMF, AMF and LROAD for both perceptional quality and engineering measured quality (PSNR and SSIM).
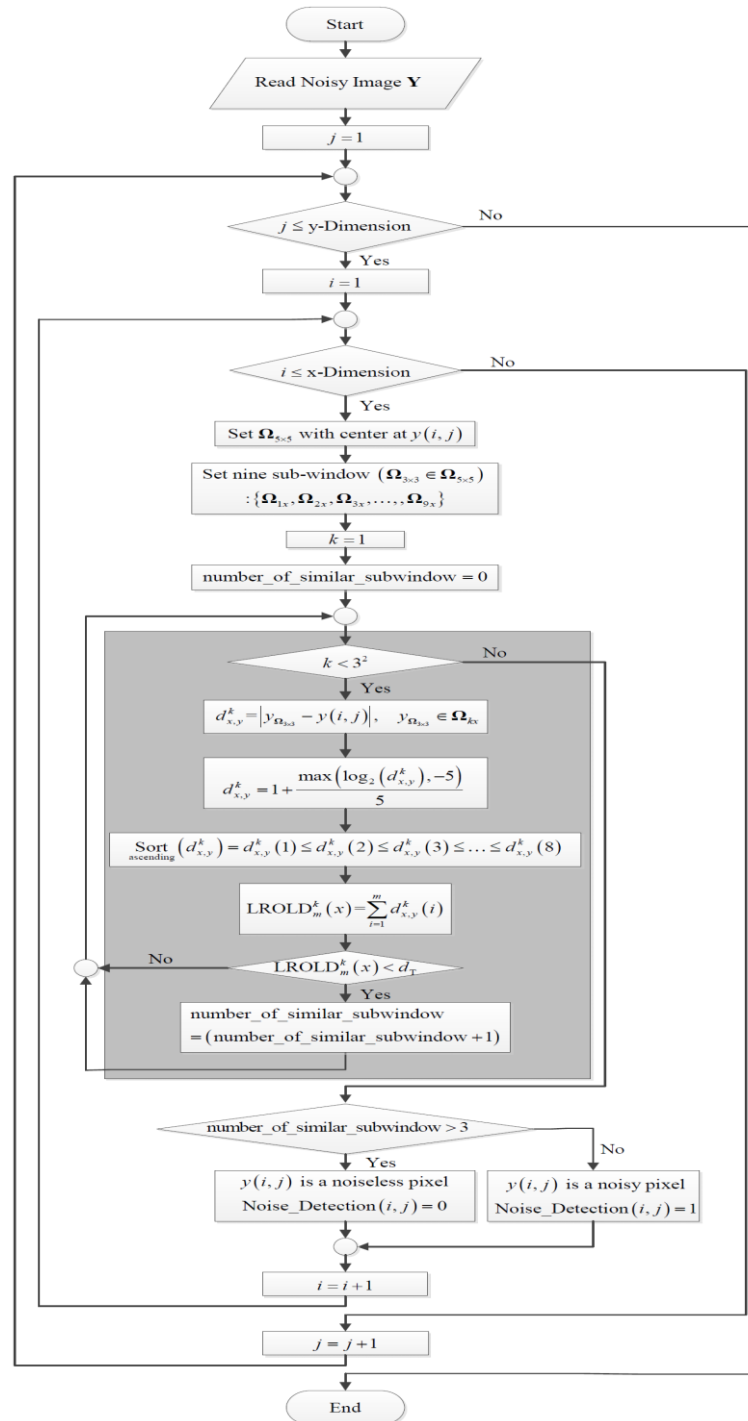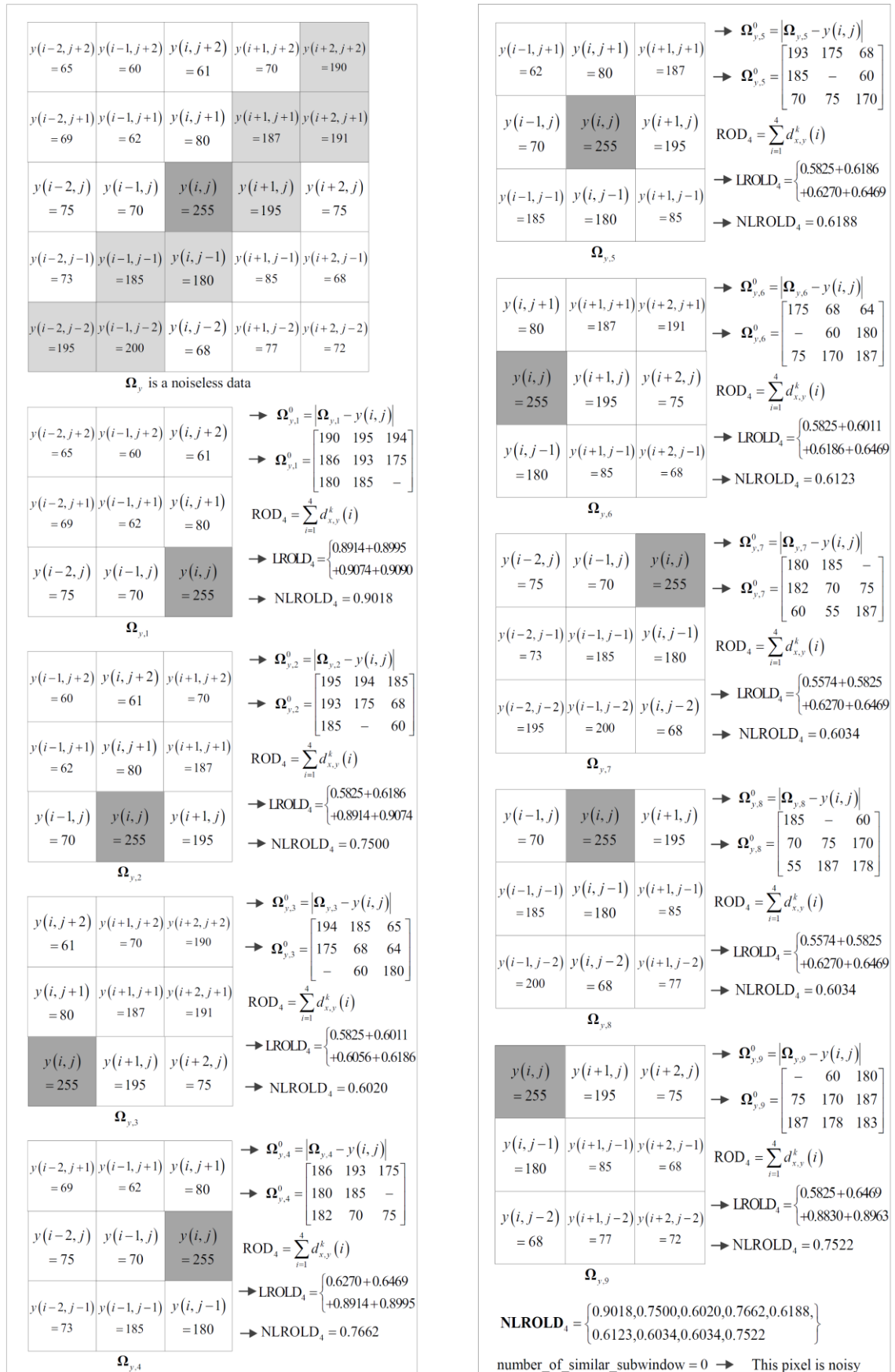
## APPENDIX



Figure 2. The scientific processing of LROLD approach

| $y(i-2,j+2)$ =65 | $y(i-1,j+2)$ =60 | $y(i,j+2)$ =61 | $y(i+1,j+2)$ =70 | $y(i+2,j+2)$ =190 |
|---|---|---|---|---|
| $y(i-2,j+1)$ =69 | $y(i-1,j+1)$ =62 | $y(i,j+1)$ =80 | $y(i+1,j+1)$ =187 | $y(i+2,j+1)$ =191 |
| $y(i-2,j)$ =75 | $y(i-1,j)$ =70 | $y(i,j)$ =255 | $y(i+1,j)$ =195 | $y(i+2,j)$ =75 |
| $y(i-2,j-1)$ =73 | $y(i-1,j-1)$ =185 | $y(i,j-1)$ =180 | $y(i+1,j-1)$ =85 | $y(i+2,j-1)$ =68 |
| $y(i-2,j-2)$ =195 | $y(i-1,j-2)$ =200 | $y(i,j-2)$ =68 | $y(i+1,j-2)$ =77 | $y(i+2,j-2)$ =72 |

$\Omega_y$ is a noiseless data

**$\Omega_{y,1}$**

| $y(i-2,j+2)$ =65 | $y(i-1,j+2)$ =60 | $y(i,j+2)$ =61 |
|---|---|---|
| $y(i-2,j+1)$ =69 | $y(i-1,j+1)$ =62 | $y(i,j+1)$ =80 |
| $y(i-2,j)$ =75 | $y(i-1,j)$ =70 | $y(i,j)$ =255 |

$$\rightarrow \Omega_{y,1}^0 = \left|\Omega_{y,1} - y(i,j)\right|$$
$$\rightarrow \Omega_{y,1}^0 = \begin{bmatrix} 190 & 195 & 194 \\ 186 & 193 & 175 \\ 180 & 185 & - \end{bmatrix}$$
$$ROD_4 = \sum_{i=1}^4 d_{x,y}^k(i)$$
$$\rightarrow LROLD_4 = \begin{cases} 0.8914+0.8995 \\ +0.9074+0.9090 \end{cases}$$
$$\rightarrow NLROLD_4 = 0.9018$$

**$\Omega_{y,2}$**

| $y(i-1,j+2)$ =60 | $y(i,j+2)$ =61 | $y(i+1,j+2)$ =70 |
|---|---|---|
| $y(i-1,j+1)$ =62 | $y(i,j+1)$ =80 | $y(i+1,j+1)$ =187 |
| $y(i-1,j)$ =70 | $y(i,j)$ =255 | $y(i+1,j)$ =195 |

$$\rightarrow \Omega_{y,2}^0 = \left|\Omega_{y,2} - y(i,j)\right|$$
$$\rightarrow \Omega_{y,2}^0 = \begin{bmatrix} 195 & 194 & 185 \\ 193 & 175 & 68 \\ 185 & - & 60 \end{bmatrix}$$
$$ROD_4 = \sum_{i=1}^4 d_{x,y}^k(i)$$
$$\rightarrow LROLD_4 = \begin{cases} 0.5825+0.6186 \\ +0.8914+0.9074 \end{cases}$$
$$\rightarrow NLROLD_4 = 0.7500$$

**$\Omega_{y,3}$**

| $y(i,j+2)$ =61 | $y(i+1,j+2)$ =70 | $y(i+2,j+2)$ =190 |
|---|---|---|
| $y(i,j+1)$ =80 | $y(i+1,j+1)$ =187 | $y(i+2,j+1)$ =191 |
| $y(i,j)$ =255 | $y(i+1,j)$ =195 | $y(i+2,j)$ =75 |

$$\rightarrow \Omega_{y,3}^0 = \left|\Omega_{y,3} - y(i,j)\right|$$
$$\rightarrow \Omega_{y,3}^0 = \begin{bmatrix} 194 & 185 & 65 \\ 175 & 68 & 64 \\ - & 60 & 180 \end{bmatrix}$$
$$ROD_4 = \sum_{i=1}^4 d_{x,y}^k(i)$$
$$\rightarrow LROLD_4 = \begin{cases} 0.5825+0.6011 \\ +0.6056+0.6186 \end{cases}$$
$$\rightarrow NLROLD_4 = 0.6020$$

**$\Omega_{y,4}$**

| $y(i-2,j+1)$ =69 | $y(i-1,j+1)$ =62 | $y(i,j+1)$ =80 |
|---|---|---|
| $y(i-2,j)$ =75 | $y(i-1,j)$ =70 | $y(i,j)$ =255 |
| $y(i-2,j-1)$ =73 | $y(i-1,j-1)$ =185 | $y(i,j-1)$ =180 |

$$\rightarrow \Omega_{y,4}^0 = \left|\Omega_{y,4} - y(i,j)\right|$$
$$\rightarrow \Omega_{y,4}^0 = \begin{bmatrix} 186 & 193 & 175 \\ 180 & 185 & - \\ 182 & 70 & 75 \end{bmatrix}$$
$$ROD_4 = \sum_{i=1}^4 d_{x,y}^k(i)$$
$$\rightarrow LROLD_4 = \begin{cases} 0.6270+0.6469 \\ +0.8914+0.8995 \end{cases}$$
$$\rightarrow NLROLD_4 = 0.7662$$

**$\Omega_{y,5}$**

| $y(i-1,j+1)$ =62 | $y(i,j+1)$ =80 | $y(i+1,j+1)$ =187 |
|---|---|---|
| $y(i-1,j)$ =70 | $y(i,j)$ =255 | $y(i+1,j)$ =195 |
| $y(i-1,j-1)$ =185 | $y(i,j-1)$ =180 | $y(i+1,j-1)$ =85 |

$$\rightarrow \Omega_{y,5}^0 = \left|\Omega_{y,5} - y(i,j)\right|$$
$$\rightarrow \Omega_{y,5}^0 = \begin{bmatrix} 193 & 175 & 68 \\ 185 & - & 60 \\ 70 & 75 & 170 \end{bmatrix}$$
$$ROD_4 = \sum_{i=1}^4 d_{x,y}^k(i)$$
$$\rightarrow LROLD_4 = \begin{cases} 0.5825+0.6186 \\ +0.6270+0.6469 \end{cases}$$
$$\rightarrow NLROLD_4 = 0.6188$$

**$\Omega_{y,6}$**

| $y(i,j+1)$ =80 | $y(i+1,j+1)$ =187 | $y(i+2,j+1)$ =191 |
|---|---|---|
| $y(i,j)$ =255 | $y(i+1,j)$ =195 | $y(i+2,j)$ =75 |
| $y(i,j-1)$ =180 | $y(i+1,j-1)$ =85 | $y(i+2,j-1)$ =68 |

$$\rightarrow \Omega_{y,6}^0 = \left|\Omega_{y,6} - y(i,j)\right|$$
$$\rightarrow \Omega_{y,6}^0 = \begin{bmatrix} 175 & 68 & 64 \\ - & 60 & 180 \\ 75 & 170 & 187 \end{bmatrix}$$
$$ROD_4 = \sum_{i=1}^4 d_{x,y}^k(i)$$
$$\rightarrow LROLD_4 = \begin{cases} 0.5825+0.6011 \\ +0.6186+0.6469 \end{cases}$$
$$\rightarrow NLROLD_4 = 0.6123$$

**$\Omega_{y,7}$**

| $y(i-2,j)$ =75 | $y(i-1,j)$ =70 | $y(i,j)$ =255 |
|---|---|---|
| $y(i-2,j-1)$ =73 | $y(i-1,j-1)$ =185 | $y(i,j-1)$ =180 |
| $y(i-2,j-2)$ =195 | $y(i-1,j-2)$ =200 | $y(i,j-2)$ =68 |

$$\rightarrow \Omega_{y,7}^0 = \left|\Omega_{y,7} - y(i,j)\right|$$
$$\rightarrow \Omega_{y,7}^0 = \begin{bmatrix} 180 & 185 & - \\ 182 & 70 & 75 \\ 60 & 55 & 187 \end{bmatrix}$$
$$ROD_4 = \sum_{i=1}^4 d_{x,y}^k(i)$$
$$\rightarrow LROLD_4 = \begin{cases} 0.5574+0.5825 \\ +0.6270+0.6469 \end{cases}$$
$$\rightarrow NLROLD_4 = 0.6034$$

**$\Omega_{y,8}$**

| $y(i-1,j)$ =70 | $y(i,j)$ =255 | $y(i+1,j)$ =195 |
|---|---|---|
| $y(i-1,j-1)$ =185 | $y(i,j-1)$ =180 | $y(i+1,j-1)$ =85 |
| $y(i-1,j-2)$ =200 | $y(i,j-2)$ =68 | $y(i+1,j-2)$ =77 |

$$\rightarrow \Omega_{y,8}^0 = \left|\Omega_{y,8} - y(i,j)\right|$$
$$\rightarrow \Omega_{y,8}^0 = \begin{bmatrix} 185 & - & 60 \\ 70 & 75 & 170 \\ 55 & 187 & 178 \end{bmatrix}$$
$$ROD_4 = \sum_{i=1}^4 d_{x,y}^k(i)$$
$$\rightarrow LROLD_4 = \begin{cases} 0.5574+0.5825 \\ +0.6270+0.6469 \end{cases}$$
$$\rightarrow NLROLD_4 = 0.6034$$

**$\Omega_{y,9}$**

| $y(i,j)$ =255 | $y(i+1,j)$ =195 | $y(i+2,j)$ =75 |
|---|---|---|
| $y(i,j-1)$ =180 | $y(i+1,j-1)$ =85 | $y(i+2,j-1)$ =68 |
| $y(i,j-2)$ =68 | $y(i+1,j-2)$ =77 | $y(i+2,j-2)$ =72 |

$$\rightarrow \Omega_{y,9}^0 = \left|\Omega_{y,9} - y(i,j)\right|$$
$$\rightarrow \Omega_{y,9}^0 = \begin{bmatrix} - & 60 & 180 \\ 75 & 170 & 187 \\ 187 & 178 & 183 \end{bmatrix}$$
$$ROD_4 = \sum_{i=1}^4 d_{x,y}^k(i)$$
$$\rightarrow LROLD_4 = \begin{cases} 0.5825+0.6469 \\ +0.8830+0.8963 \end{cases}$$
$$\rightarrow NLROLD_4 = 0.7522$$

$$\mathbf{NLROLD}_4 = \begin{cases} 0.9018, 0.7500, 0.6020, 0.7662, 0.6188, \\ 0.6123, 0.6034, 0.6034, 0.7522 \end{cases}$$

number_of_similar_subwindow = 0 → This pixel is noisy

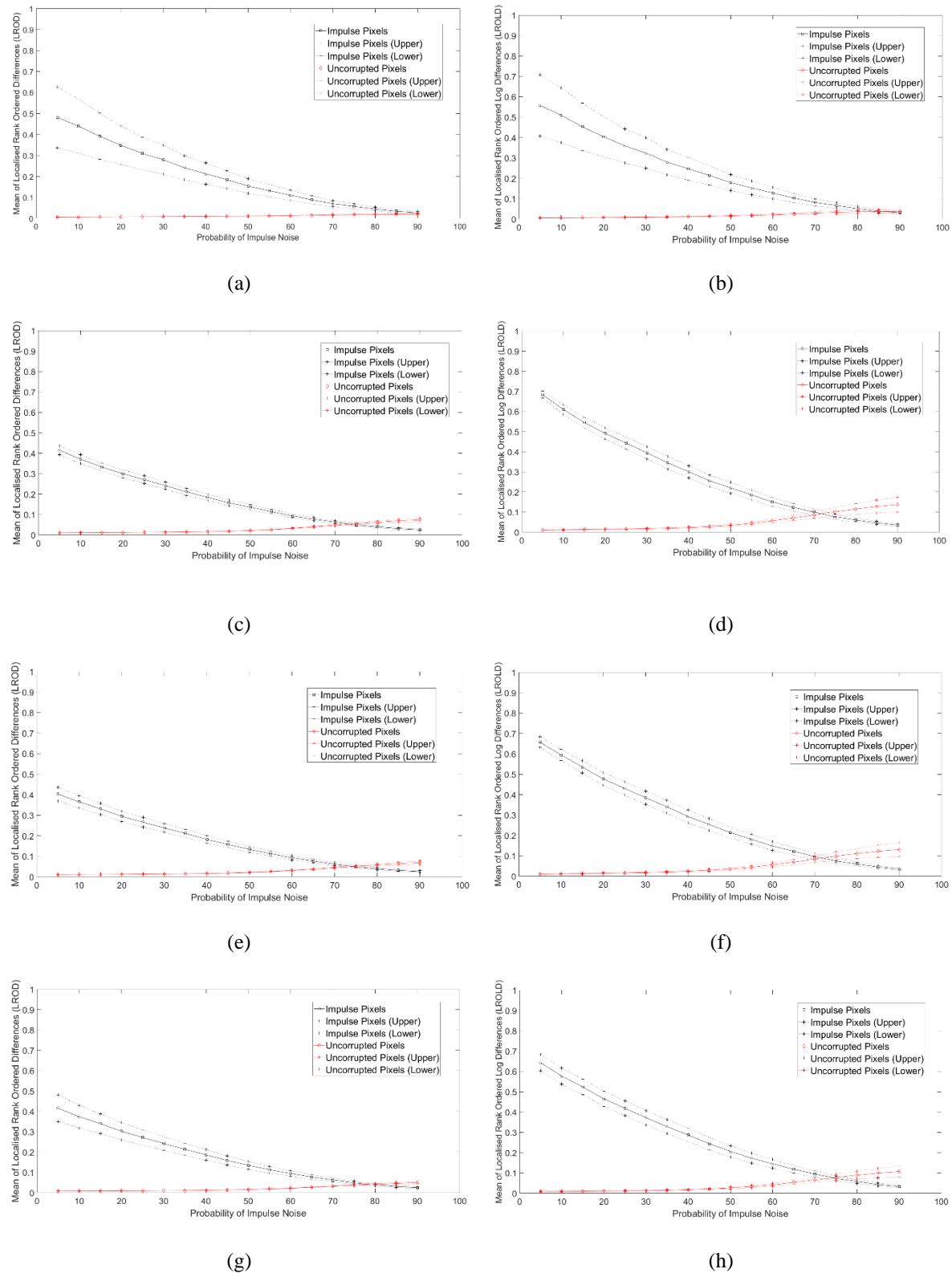Figure 3. The example of LROLD approach process where $y(i,j) = 255$ is outlier

Figure 4. The scientific result of the first and second moment statistical specifications (a) The LROAD of mean and SD: Girl, (b) The LROLD of mean and SD: Girl, (c) The LROAD of mean and SD: Lena, (d) The LROLD of mean and SD: Lena, (e) The LROAD of mean and SD: Pepper, (f) The LROLD of mean and SD: Pepper, (g) The LROAD of mean and SD: F16, and (h) The LROLD of mean and SD: F16

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